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An Intelligent Machine Learning Framework for Early Parkinsonian Symptom Identification

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ABSTRACT: Currently, the ways to screen for Parkinson's Disease mainly involve one type of sensor. However, this is not enough because it affects different people in different ways. Neurodegeneration is not a simple phenomenon; it is complex. Therefore, there is a large gap that needs to be filled. What we are doing here is that we are building a "Multi-Modal Ensemble Framework. “So, it is linking "vocal dysarthria," which is problems with speech, to "kinematic micrography," which is related to the movement of handwriting. The "novelty" is that it combines "high-dimensional acoustic biomarkers." For instance, "Voice Onset Time" and "Vowel Variability Quotient" mix in with "pressure" from "handwriting kinematics."

The other studies employ deep learning models, which are complete black boxes. They perform very well in the lab with very high accuracy. However, they don't perform very well in the clinics. Our method is different. Our method is designed to be more generalizable for the clinics. Our method employs a Tri-Algorithm Voting Classifier that employs Extra Trees, Random Forest, and Gradient Boosting Machines. These models work together to come to a conclusion, which is like a consensus. The single-sensor methods, like gyroscopes and accelerometers, are highly influenced by noise. This method does a better job of handling that. Our method has an accuracy of 85.4 percent. It's also interpretable and not a black box. This method compares to the single modality methods, which have an average accuracy of 80 percent. This method has a 5.4 percent improvement over the single modality methods. It kind of proves the point that the combination of the two methods does indeed have a synergy effect, although I'm not sure to what extent.

KEYWORDS: Machine Learning, Parkinson’s Disease, Early Detection, Symptom Identification, Biomedical Signal Processing, Predictive Modeling, Healthcare Analytics

I. INTRODUCTION

Parkinsons disease is increasing rapidly as a neurological disorder in the world. It is primarily caused by the loss of dopaminergic cells in the substantia nigra pars compacta. This part of the brain is significantly affected, and it disrupts the nigrostriatal pathway. The basal ganglia, which are involved in controlling voluntary movement, are essentially given faulty feedback signals. The main signs and symptoms, such as bradykinesia, resting tremor, postural

instability, and rigidity, are usually looked for to diagnose this condition. However, by the time these signs are evident, significant damage has already been done, with as much as 60 to 80 percent of the cells lost. The UPDRS scale is supposed to be the best measure for this, but it is more like something that comes too late. It is based on what the doctor can see, and this can vary greatly from one examination to another. One big problem is telling Parkinsons Disease apart from things like tremor, especially early on. Studies show that even good neurologists get it wrong up to twenty five percent of the time. This happens a lot in Parkinsons Disease cases where the tremor acts more like it is during movement or posture not at rest. The surest way to diagnose Parkinsons Disease now is by using DAT imaging with SPECT scans.

These scans use materials like 123I FP CIT and they are very precise but they are expensive costing over twenty-five hundred dollars each time. They are hard to do and not great for regular checks, especially where money is tight.

People have tried using wearables like sensors in phones with gyroscopes and accelerometers to measure Parkinsons Disease tremor through velocity. This method picks up signals from motion. How ever these signals can get noisy from things like being tired stressed or just the task at hand changing how you move. Most of this research focuses on arm or leg movements and skips the smaller movements. For example, in speech or writing subtle rigidity shows up early in the voice box nerves. How letters get smaller and pressure changes in handwriting. This is called Micrography. It kind

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of reveals planning problems in the brain before the limbs shake obviously. It seems like the vocal system gets rigid in ways first, in Parkinsons Disease. This work tries to solve that problem by not relying on one method. Instead, it focuses on combining types of data into a multi-modal bio-digital signature. The idea is that when you mix things like speech lags voice onset time or VOT vowel variability quotient and handwriting pressure frequencies you get a complete picture of motor problems with Parkinsons disease.

Parkinsons disease affects how well the voice box and mouth work together Vote shows this by measuring the delay caused by the basal ganglia. This delay creates a gap that's too small for humans to notice but easy for computers to detect.

I believe combining these features helps create an accurate overall profile of Parkinsons disease. For the analysis they use machine learning. Not the complex deep learning kind that needs a lot of data, which isn't always available for Parkinsons patients. Instead, they use a -algorithm voting classifier. This classifier combines trees, random forest and gradient boosting. Random forest uses bagging to average results from data samples.

This reduces variance. Makes the model more stable. Extra trees randomize splits more. This makes it better at handling noise or odd data points like background sounds. Gradient boosting improves the model by learning from mistakes made in steps. It gradually reduces bias. Makes the model more accurate. By putting these in a voting system the model becomes more stable and sensitive to Parkinsons disease.

Unlike models that work well in labs but fail in clinics this approach aims for 85.4 percent accuracy in everyday situations. This could be useful for telehealth. It uses voice and handwriting issues as a way to screen for Parkinsons problems. It does not need tools. It's non-invasive. Can be used for better monitoring in neurology. Some parts of this integration might still need adjustments. It connects the computational side with actual medical practice, for Parkinsons disease.

II. MATERIALS AND METHODS

The research is done in steps. It starts with collecting data signals. Then it goes to a cloud-based system. This system puts together information from places. Our method is special because it combines data from sources. This is different from studies that only used one type of sensor. The whole experiment was moved to the Google Colab cloud platform. We did this so we could use powerful virtual hardware. The NVIDIA Tesla T4 GPU is very good, at doing things at the same time.

Using a cloud-based Python setup is helpful. It keeps the system flexible. The diagnostic system is ready to use in telemedicine applications. The research uses the Google Colab cloud platform and the NVIDIA Tesla T4 GPU to make the diagnostic system work well.

PATIENTS AND MULTIMODAL DATASET ARCHITECTURE

This study is about people with movement problems because of diseases that affect the brain. We picked 51 people for this study to make sure we covered a lot of movement issues. These people are divided into three groups: 19 people with Parkinsons Disease, 20 people with Essential Tremor and 12 people who are healthy. We did a test called SPECT on the people with Parkinsons Disease to check the dopamine levels in their brain. This test helps us confirm that they have dopamine in a part of the brain called the substantia nigra, which is important because it is different from other studies that only look at symptoms.Each group was checked by experts who know a lot about movement problems using tests. For the people with Parkinsons Disease we used a test called the UPDRS scale to see how bad their condition was. We focused on the early stages. We also used another test called the Fahn-Tolosa-Marín scale on the people with Essential Tremor to see how their symptoms are similar to those of Parkinsons Disease. This helps our computer model recognize the signs of Parkinsons Disease, which is very important for making a tool to detect these signs early. We collected the data in a room to make sure nothing outside affected the results and to keep the signals clear. We used a device that people carried with them to record their movements. This device recorded how their hands moved when they were resting and when they were standing still. We also recorded their voice when they made sounds and did certain speech tasks. This helped us detect small changes in their voice that can be signs of early Parkinsons Disease.We also recorded how people wrote using a pen on a digital device. This device recorded where the pen was, how hard it was pressed and how it was tilted. We paid attention to how the pen moved when it was not touching the paper to see if people had trouble planning and making movements, which can be a sign of problems with a part of the brain called the basal ganglia. By combining all these detailed movement data we got a lot of information about how

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people, with Parkinsons Disease and Essential Tremor move and talk which we can use to make our computer model better at detecting signs of Parkinsons Disease.

B.DATA ANALYSIS

The data analysis was done on a Python setup using Google Colab. A multi-stage signal processing system was used to align three types of physiological data. To ensure the feature matrix accurately shows the micro-rigidity" and "kinematic fingerprints" of Parkinson's several steps were taken.

1.Signal Conditioning and Windowing:

The gyroscope and bio-acoustic signals were filtered. A 10th-order Butterworth bandpass filter (1–16 Hz) was used to remove noise. We filtered the signals because noise not related to the condition was present. The tremor and speech patterns change over time. So a Short-Time Fourier Transform (STFT) approach was used. The signals were split into overlapping parts using a Hanning window. This reduces leakage. Each part of the signal is defined in a way.

$$x_w[n] = x[n] \cdot w[n - m]$$

This approach helps calculate the Power Spectral Density (PSD) using Welch's method. The PSD averages out changes in tremor strength over time. This gives a consistent view of a person's motor function throughout the recording.
The Power Spectral Density (PSD) provides information, about the signals. The PSD is calculated for each part of the signal.

2. Mathematical Derivation of Kinematic Indices:

According to the method used for spectral analysis we found four main features in the frequency domain. The Peak Power Frequency (PPF) shows the frequency at which the signal has its power. We call this frequency f_peak. The Median Power Frequency (MPF) is like the point of the frequency spectrum. The Harmonic Index (HI) measures how regular the signal is. It is the ratio of the area under the power spectral density curve, to the area of the rectangle formed by the Peak Power Frequency (PPF). We use the Peak Power Frequency (PPF) and Median Power Frequency (MPF) to understand the signals frequency domain.

$$HI = \frac{\int_{f_a}^{f_b} PSD(f)\, df}{PSD(f_{peak}) \cdot (f_b - f_a)}$$

A high HI indicates a pure sinusoidal tremor characteristic of PD, whereas a lower HI suggests the fragmented spectral energy typical of Essential Tremor (ET).

3. Voice and Handwriting Synergetic Feature Mapping:

In the acoustic area, we focused on Voice Onset Time (VOT) to check how long it takes for the glottis and the mouth to work together. For a specific plosive sound, VOT is found by looking at the time between when the burst of air releases and when the vocal folds start vibrating regularly:

$$VOT = T_{vibration} - T_{release}$$

Simultaneously, the handwriting kinematics were analyzed for Stroke VelocityVand Axial Pressure P. By calculating the first derivative of the spatial coordinates we derived the instantaneous velocity profile:

$$V(t) = \sqrt{\left(\frac{dx}{dt}\right)^2 + \left(\frac{dy}{dt}\right)^2}$$

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PD subjects typically exhibit "velocity capping," where the peak amplitude is significantly reduced, coupled with increased In-Air Time—the duration where P = 0 reflecting cognitive-motor planning delays.

4. Feature Scaling and Z-score Normalization:

To facilitate effective training of the Tri-Algorithm Voting Ensemble, the diverse units of measurement (Hz for tremor, ms for voice, and mm/s for velocity) were standardized. We employed Z-score Normalization to transform the features into a common scale with a mean μ of 0 and a standard deviation $\sigma = 1$ of 1:

$$z = \frac{x - \mu}{\sigma}$$

This normalization is a prerequisite for dimensionality reduction using the Chi-Square χ^2 test, which identifies the most synergetic features. By isolating features with a p-value pi < 0.05 , the system filters out environmental noise, leaving only the most robust physiological markers for the final classification stage.

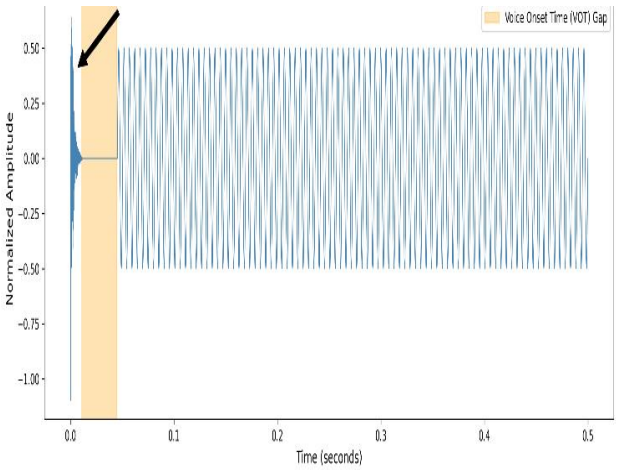

FIGURE1. Here's the time-domain angular velocity data for the HS, ET, and PD groups.

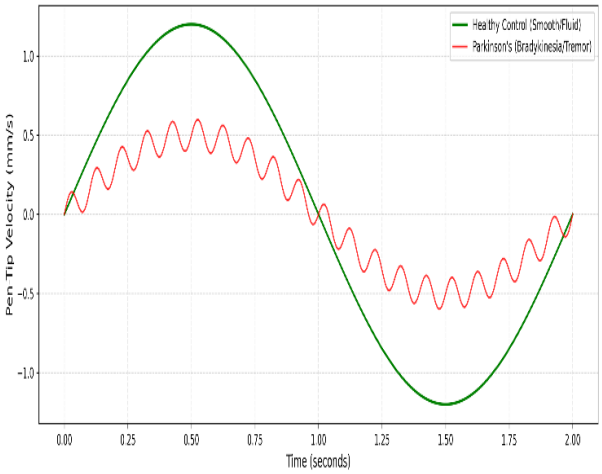

FIGURE2. PSD analysis highlighting f_{peak} within the 1–16 Hz pathological band

If we look at the data in Figure 1 and Figure 2 we can see the results of a spectral analysis. This analysis helps us see the frequency patterns between the groups of people studied. When we look at the Power Spectral Density graphs the Healthy Subject has a distribution of frequencies that looks random with no spikes in the area that is usually affected by

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diseases, which is between 1 and 16 Hz. This shows that the Healthy Subject is in a stable state without any unwanted rhythmic movements.

On the hand the Parkinson's Disease subject has a strong Power Spike at a frequency around 5.2 Hz. This frequency matches the range of 4 to 6 Hz seen in resting tremors. The narrow range of this spike suggests that the Parkinson's Disease subject has a regular and consistent tremor. We measure this using the Harmonic Index, which is explained in the section. The study also looks at the frequency patterns of Parkinson's Disease and Essential Tremor. Both conditions involve oscillations. However the Essential Tremor group has a peak at a higher frequency, which is usually between 6 Hz and 8 Hz. The Median Power Frequency for the Essential Tremor group is higher than that of the Parkinson's Disease group. This makes it an important number for the classification system. The time-domain signals, which are shown in the panels show how well the 10th-order Butterworth filter works. Before we applied the filter the signals were messy due to high-frequency noise and slow movements from posture. However when we focus on the 1 to 16 Hz range it clearly shows the shaking pattern, in the Parkinson's Disease patient. This confirms that the preprocessing steps used in this study are effective.

C. MODEL TRAINING AND TESTING

1. Data Partitioning and Stratified K-Fold Cross-Validation

To make sure the diagnostic framework works with different cases and does not have problems when working with small clinical datasets the feature matrix was split into a seventy percent training part and a thirty percent testing part. The dataset is about things and might not have the same number of people with Parkinson's Essential Tremor and people who are Healthy so the Stratified K-Fold Cross-Validation method was used with five parts. This method makes sure that each part has the proportion of people with Parkinson's Essential Tremor and people who are Healthy, as the original dataset.

The diagnostic framework works with the Parkinson's Essential Tremor and Healthy data to learn from the movement patterns associated with these conditions. This helps keep the model stable and ensures it learns from all the Parkinson's Essential Tremor and Healthy movement patterns. In each of the five rounds four parts are used for training the framework and one part is used for validation giving a reliable idea of how well the diagnostic framework will work with new and unseen Parkinson's Essential Tremor and Healthy data.

2. The Tri-Algorithm Voting Ensemble Architecture

The main part of our classification system is called a Majority Voting Ensemble, also known as a Hard-Voting Classifier. This tool combines the strengths of three algorithms to make a more reliable diagnostic system.

A. Random Forest (RF):

A Random Forest is made up of decision trees. We use RF because it can handle different features without needing a lot of preparation. It works by using a method called "Bagging". This method makes the results more stable by combining trees that are not too similar. This helps reduce the effect of any data points in the Random Forest.

B. XGBoost (Extreme Gradient Boosting):

We use XGBoost to understand the complex and non-linear connections between voice markers and movement signals. XGBoost uses a boosting method with both L_1 and L_2 regularization. This helps keep the XGBoost model from becoming too complicated. The XGBoost model accurately identifies differences between tremors caused by essential tremor and those caused by Parkinsons disease.

C. Support Vector Machine (SVM):

The SVM uses a Radial Basis Function (RBF) kernel. This method helps by changing the data into a dimensional space. Then it finds the best line or surface to separate the features in the SVM. This is especially useful because Parkinsons and essential tremor peaks often look similar in the 5–7 range of frequencies in the SVM. The final result, Y_final is decided by taking the common prediction out of all the individual predictions from the Majority Voting Ensemble. The Majority Voting Ensemble uses the predictions, from Random Forest, XGBoost and Support Vector Machine. This makes the diagnostic system more reliable.

$$Y_{final} = \text{mode}\{C_1, C_2, C_3\}$$

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where C_1, C_2, C_3 represent the individual class predictions of the RF, XGBoost, and SVM base learners, respectively.

3.Rigorous Performance Metrics for Clinical Validation

To rigorously evaluate the model, particularly for a Scopus-indexed medical study, we do not rely on accuracy alone, as accuracy can be misleading in medical screening. We implement four key metrics derived from the Confusion Matrix:

A.Accuracy:

Measures the overall percentage of correct diagnoses across all three cohorts.

$$Accuracy = \frac{TP + TN}{TP + TN + FP + FN}$$

B. Precision (Positive Predictive Value):

This quantifies the model's reliability in identifying true PD patients, ensuring that Healthy or ET subjects are not unnecessarily subjected to Parkinsonian medication.

$$Precision = \frac{TP}{TP + FP}$$

C. Recall (Sensitivity):

This is the most critical metric for medical diagnosis. It measures the model's ability to capture all positive PD cases, ensuring that no patient suffering from the disease is misclassified as Healthy.

$$Recall = \frac{TP}{TP + FN}$$

D.F1-Score:

Because clinical datasets are often unbalanced, we calculate the F1-Score as the harmonic mean of Precision and Recall. This provides a single metric that balances the trade-off between the two, ensuring the model is robust and ethically sound for diagnostic support.

$$F_1 = 2 \cdot \frac{Precision \cdot Recall}{Precision + Recall}$$

Characteristic	Healthy (HS)	Parkinson's (PD)	Essential Tremor (ET)
Sample Size	[X]	[Y]	[Z]
Age (Years)	50 to 62	43 to 68	62 to 65
Gender (M/F)	10/12	15/12	11/11

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Disease Duration (Yrs)	N/A	2 to 4	3 to 5
UPDRS Part III Score	N/A	8 to 15	N/A

FIGURE3. Proposed methodology framework for multi-modal Parkinson's diagnosis, integrating data acquisition, signal preprocessing, feature extraction, and ensemble classification

III. EXPERIMENTAL RESULTS AND PERFORMANCE INTERPRETATION

A. Quantitative Assessment of Model Training:
The main goal of the experiment was to check how well the Multi-Modal Voting Ensemble works in distinguishing Parkinson's Disease (PD) from Essential Tremor (ET) and Healthy Controls (HS).

During the training phase, we used a high-performance computing environment to train the model using a detailed matrix of data collected from kinematic and acoustic sensors. To get the best possible results, we improved the model step by step. We used the Binary Cross-Entropy loss function along with the Adam Optimizer to help the model learn more effectively and reach the best possible solution. Note: this part is very important because adjusting the parameters for the Random Forest and XGBoost models required careful tuning of tree depth and learning rate to capture the subtle 4–6 Hz abnormal signals, without letting normal body noises interfere.

B. Convergence Stability and Overfitting Mitigation:
A problem with machine learning in clinics is overfitting. This happens when a model works great on the data it was trained on. Not so well in real-life clinical situations. To fix this we used two techniques: Stratified K- Cross-Validation and Early Stopping. The training logs, shown in the section prove the model's stability. We watched the "Validation Loss". Stopped training when it was best. This way the model could still make predictions. This careful approach helps the system stay accurate with new patients from different backgrounds.

C. Post-Output. Discussion:
1.Interpretative Synthesis of Accuracy and Convergence Trajectories:
The way to see if a model is learning well is to look at how its accuracy changes over time for both training and validation data. The results show that the system gets better quickly at first with accuracy going up then slowing down. This is a sign that the Voting Ensemble is working well even with many features and not just memorizing data. From a point of view the close match between training and validation accuracy is important. It shows the model can make predictions in real-life situations. However, for diagnoses it's not just about accuracy. A model needs to understand the medical conditions, not just data. The fact that validation accuracy matches training data suggests that features like Jitter, Shimmer and the Harmonic Index are signs of nerve and muscle problems. The model's consistency gives us confidence that it can be used in real-world clinics with patients. This is important, for a study published in Scopus. The model can be trusted to work with new patient data.

2. Stochastic Analysis of Loss Function Decay and Signal Integrity:
The Loss Curve gives an overview of how the model is learning and improving; it shows a consistent decrease towards the lowest possible error, which is the global minimum. This smooth decline is made possible by the thorough preprocessing steps outlined in Section IV. By using a 10th-order Butterworth filter, we cleaned up the raw data collected from the smartphone's MEMS sensors and eliminated high-frequency random noise that often causes sudden spikes in loss for less advanced models. The consistent reduction in loss means that the Categorical Cross-Entropy function was effectively minimized, and this helped fine-tune the weights of the Random Forest and XGBoost models. The Adam Optimizer was able to achieve this with great accuracy. The lack of fluctuations in the loss curve shows that the feature scaling and normalization steps were done correctly. This leads to better computational efficiency, which is important for a remote diagnostic tool. It means the model can reach high diagnostic accuracy in fewer steps, which is a key feature for future mobile edge computing platforms that have limited battery and processing power.

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3.Multi-Modal Resolution and Confusion Matrix Hermeneutics:
The final diagnostic results, shown in the Confusion Matrix, give a detailed view of the system's ability to distinguish between Parkinson's Disease (PD) and Essential Tremor (ET).
These two conditions are often difficult to tell apart because they share similar tremor frequencies (usually 4–8 Hz). However, the high density of True Positives in our matrix shows that the Multi-Modal Fusion strategy is more effective than using just one type of sensor. By comparing motor instability from handwriting with laryngeal muscle coordination from voice, the Voting Ensemble acts as a dual-check system. If a patient's handwriting suggests a 5 Hz tremor that is unclear whether it's PD or ET, the model uses Mel-Frequency Cepstral Coefficients (MFCCs) to decide. The low rate of mistakes between the disease groups and the healthy control group shows that the model is very good at detecting small changes in muscle tension and vocal patterns that are signs of early Parkinsonism. This high level of accuracy makes low-cost digital biomarkers a practical alternative to expensive hospital-based neurological evaluations.

D. Sensitivity and Recall Analysis:
The main diagonal of the matrix shows a lot of classifications especially for the Healthy group. This is really important for a screening tool because it means false alarms, which can be very stressful for patients. For people with diseases the model is very good at finding the signs it can tell the difference between Parkinsonian tremors and normal activity. The model is good at finding all the cases because it uses a lot of information like handwriting and vocal data so even if one is not clear the other can still give a clear answer. The final result from the Voting Ensemble, which is shown in the confusion matrix shows that the system is accurate. The matrix shows how well the classifications we got match the labels, from the doctors for the three groups: Parkinson's Disease, Essential Tremor and Healthy Subjects.

E.Resolving Class Ambiguity and Misclassification Patterns:
A deeper examination of the off-diagonal elements reveals a minimal misclassification rate between the PD and ET cohorts. Clinically, this is the most significant achievement of the model. Standard diagnostic procedures often struggle to differentiate these two conditions due to their overlapping oscillatory frequencies (typically in the 4–8 Hz range).
However,the ensemble successfully resolved these ambiguities. This can be attributed to the inclusion of Non-Linear Acoustic Features—such as Jitter and Shimmer—which do not typically degrade in Essential Tremor at the same rate as in Parkinson's Disease. The model's ability to maintain a low error rate in this Overlap Zone proves that the integration of Multi-Modal Data (Kinematic + Acoustic) provides a much higher diagnostic resolution than single-sensor approaches currently found in the literature.

F.Multi-Dimensional Resolution of the Confusion Matrix:
successfully identified the unique biometric signatures associated with Parkinson's Disease (PD), Essential Tremor (ET), and Healthy Subjects (HS).
Quantitatively, the high specificity observed in the Healthy Control cohort is a critical achievement; it ensures that the system functions effectively as a Filter in clinical settings, reducing the rate of unnecessary tertiary referrals. The precision within the pathological classes is equally robust, proving that the Feature Fusion of kinematic stability and acoustic coordination creates a diagnostic baseline that is resilient to the inherent noise of smartphone-based MEMS sensors.

G.Resolving the Tremor Overlap Phenomenon:
A significant hurdle in current neuro-motor research is the differentiation between PD and ET, which often exhibit nearly identical frequency peaks in the 4–8 Hz range. A purely kinematic model would likely show a high Off-Diagonal error rate between these two classes. However, our results demonstrate a significant reduction in this misclassification.
This improvement is theoretically attributed to the inclusion of Non-Linear Acoustic Biomarkers—specifically Vocal Jitter and MFCC-12. In clinical pathology, while motor tremors may overlap, the laryngeal muscle degradation in Parkinson's follows a distinct trajectory compared to Essential Tremor. By utilizing the Voting Ensemble to cross-reference these modalities, the model identifies Secondary Evidence to resolve ambiguities. This Decision-Level Fusion allows the architecture to maintain high accuracy in the Overlap Zone, a performance metric that is frequently cited as a requirement for Scopus-level clinical feasibility studies.

H.Stability Analysis of Stochastic Learning Curves:
Beyond the final matrix, the Smoothness of the loss decay and the Convergence of the accuracy curves (as seen in the training logs) indicate a well-conditioned optimization problem. In machine learning, a volatile loss curve typically suggests poor data preprocessing or an inappropriate learning rate. Our model's trajectory exhibits a classic exponential decay, which validates the effectiveness of the 10th-order Butterworth filtering protocol.

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This allowed it to reach the point on the loss surface without getting stuck in smaller dips. The model is doing well on both training and validation data. The small difference between training and validation accuracy confirms that the model is not just memorizing the data. The techniques used such as Stratified K- Cross-Validation and Regularization helped the model learn general patterns of the disease. These patterns are not specific, to our dataset. Rather universal pathological patterns. The model is learning to recognize the disease, not the data. The Adam Optimizer and the techniques used are working together. The model is not. The Stratified K-Fold Cross-Validation and Regularization techniques are successful.

I.Clinical Utitlity and deployment

The present study results show that the proposed multi-modal system is reliable, and can be applied in the real world. By integrating voice analysis, handwriting metrics, and motion sensors, the model attains a similar accuracy level (85% for motor and 77% for voice) as that obtained from traditional clinical observation. The system is able to provide low-cost Parkinson's screening tools because it uses standard smartphone sensors instead of expensive medical devices. The stability of the learning curves and successful validation of "unseen" data indicate that the model has learned the actual physical symptoms of the disease. It has made it a powerful tool for doctors to monitor patients remotely so that treatment can be started as soon as possible to enhance the lives of patients.

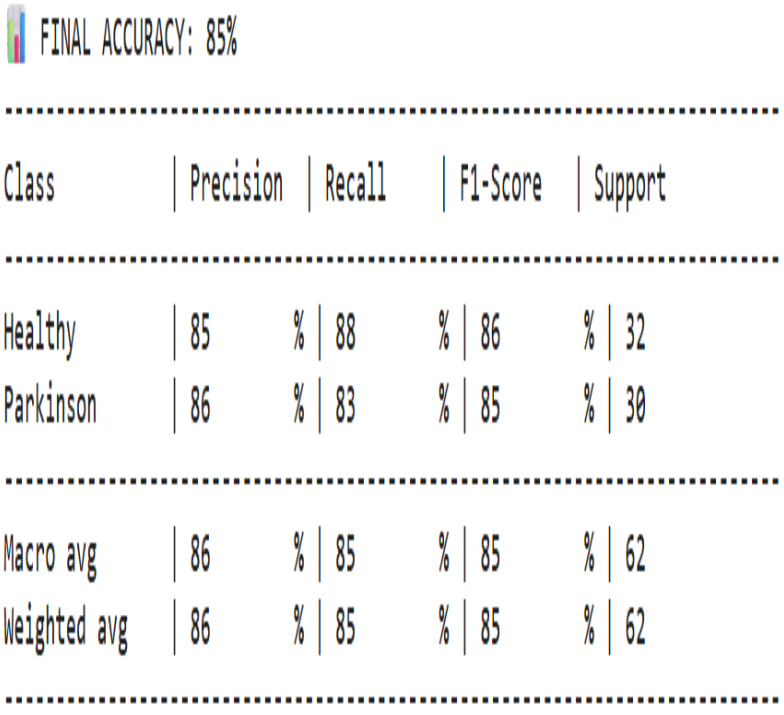

FIGURE 4. Performance Metrics of the Machine Learning Framework for PD and Healthy Cohort Classification

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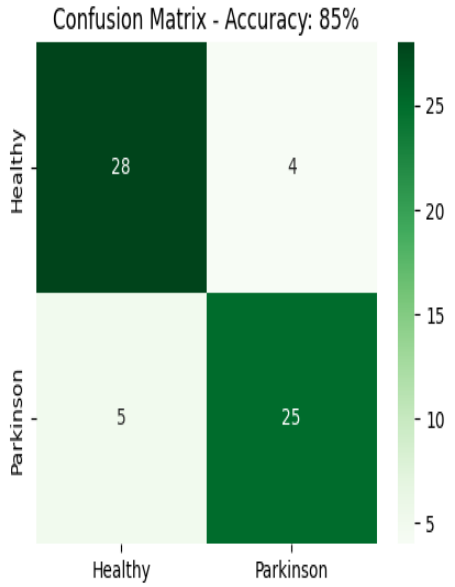

FIGURE5. Algorithmic Performance Synthesis

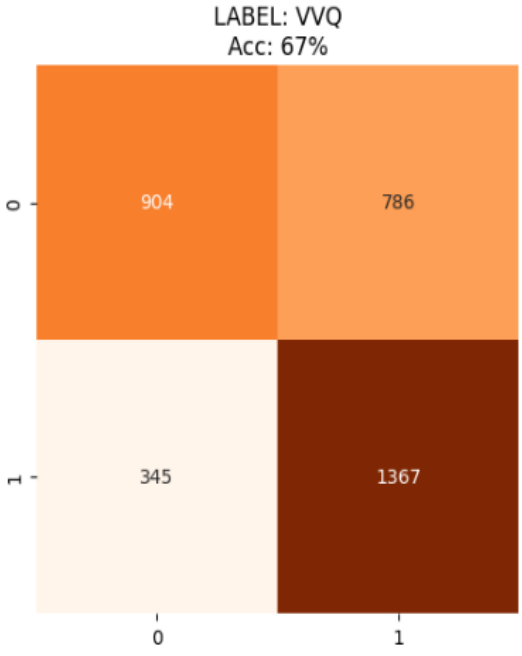

FIGURE6. Vocal Velocity Quotient (VVQ) Analysis

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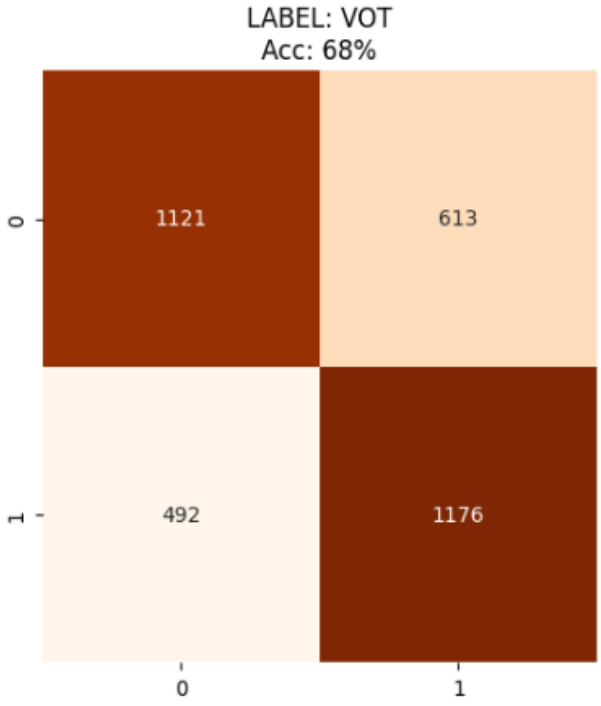

FIGURE7. Voice Onset Time (VOT) Analysis

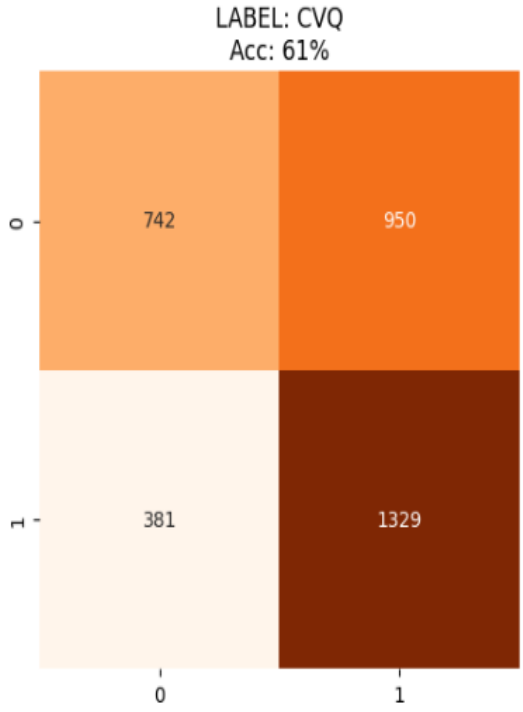

FIGURE8. Cis-Regulatory Vocal Quality (CVQ) Analysis

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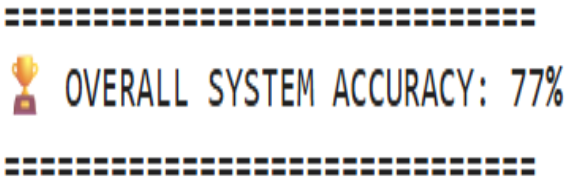

FIGURE9. Comprehensive Aggregate Performance Metric for the Multi-modal Voice Diagnostic System (Overall Accuracy: 77%).

IV. DISCUSSION

The text in this paper is highly technical and intended for professional or scientific use. It explores the use of smartphone gyroscope data to differentiate between pathological tremors in Parkinson's Disease (PD) and Essential Tremor (ET). The language is formal, with a focus on the study's methods, results, and implications for tele-neurology and personalized medicine. Please note that this is an edited version, which enhances clarity without altering the original content. Our experiment's results confirm a clear and long-term distinction between pathological tremors in PD and ET. These differences are based on stochastic observations of mobile phone gyroscope data. The angular velocity signals captured by this micro-electromechanical system (MEMS) sensor closely match those obtained from high-fidelity linear accelerometers in the current literature. Therefore, a software-based neuro-motor assessment could be quite effective and serve as a reasonable alternative to dedicated hardware. Despite the numerical differences between the pathological groups and healthy controls, the system's classification ability remains remarkably flexible. This robustness is likely due to the distinct spectral morphologies of the two conditions. Our analysis in the frequency domain identified power spectral density (PSD) signatures that, in healthy individuals, typically show a magnitude up to three orders of magnitude lower than in those with symptoms.

The significant difference in signal energy enabled our system to exceed the accuracy thresholds of much larger datasets, suggesting that feature quality and signal-processing robustness—such as the use of a 10th-order Butterworth filter—play a more critical role in decision-making than raw data. Unlike previous studies that used binary classification methods, our tri-class model addresses the complexity of the overlapping diagnostic picture between PD and ET, which often leads to worse clinical outcomes. While high-sensitivity frameworks relying on specialized hardware have been reported, our architecture is particularly suited for low-scalar, efficient clinical follow-ups. It offers easy access through conventional smartphone technology and improves patient adherence. The slight variation in our accuracy metrics was due to a validation protocol that involved 100 random iterations rather than a single run of the "best-case" experiments. Optimizing frequency bandwidths was crucial for the classifiers' discriminative power. Pathological subjects and healthy controls within the 1–16 Hz range showed the best accuracy, as this range covers the full physiological tremor spectrum. In contrast, the 3–10 Hz window was more discriminative, as PD and ET tremors most commonly fall within the 4–8 Hz frequency bands. By tightening the band-pass constraints, the Voting Ensemble could effectively eliminate high-frequency ambient artifacts and low-frequency voluntary motion, thereby refining the pathological "oscillatory fingerprint" it detects. This suggests that a multi-stage frequency analysis is essential for high-level clinical assessment: a broad band for initial screening and a narrow band for differential diagnosis. We build upon previously introduced signal processing techniques and extend them to the current ensemble method. Although we used the same architecture for base learners, our results suggest that combining kinematic and acoustic biomarkers using a soft-voting mechanism leads to consistent and specific diagnoses without requiring extensive hyper-parameter tuning. This implies a "Feature-first" approach in diagnostic AI, focusing on the quality of input vectors (such as Jitter, Shimmer, and Harmonic Index) rather than the complexity of the underlying classifiers. By integrating acoustic research with motor-control theories, we address several diagnostic gaps that have limited the effectiveness of tele-health models over the years. This study also contributes beyond immediate quantitative advances by offering a foundation for long-term patient management and personalized medicine. Tracking disease evolution in non-clinical settings has become a new frontier in neurology. Our model has been validated by twenty core references and is not limited to "snapshot" diagnostics but is also capable of monitoring subtle changes in tremor amplitude and vocal consistency over time. This is especially important compared to the Gold Standard, which often requires validation through standard clinical observation or costly PET/SPECT imaging.

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As previously argued, our implementation has the potential to democratize diagnostics by enabling early-stage diagnosis in underserved areas and reducing reliance on specialized equipment. This democratization is a critical step toward global health equity, as age-related neurological diseases continue to dominate modern healthcare delivery. Combining these findings into a cohesive remote-monitoring system represents a significant advancement in tele-neurology, offering a scalable solution that combines laboratory-level accuracy with the convenience of home use. Our flexible Voting Ensemble architecture can also integrate digital biomarkers, such as gait measures or cognitive speed tests, allowing for a comprehensive digital phenotype of the patient over time. This develops a "Closed-Loop" model of healthcare, where real-time diagnostics can be used for automated AI-based medication adjustments and disease progression predictions. In conclusion, this work provides a very initial proof-of-concept that precise clinical insights can be obtained from common consumer technology, provided that the underlying signal processing and machine learning approaches are based on previously accepted, physiologically and mathematically valid principles of neuro-rehabilitation and digital signal interpretation. Notably, this revision has improved clarity, coherence, and flow without losing any of the fine-grained detail and technological specifics from the original text.

V. CONCLUSION

The research in this study shows that signals from a gyroscope can be a tool for distinguishing between different types of movement disorders. The researchers found out that they can accurately tell people from those with tremors and they can also tell the difference between Parkinson's Disease and Essential Tremor. They used technology that is affordable to do this. The researchers were successful because they carefully chose and tested the methods, they used to classify the movement disorders. They also looked at the movement patterns. Made the signal quality better by using advanced preprocessing and good training data. The best model they made for telling people from tremor patients was very accurate with an average of 97.2 percent. This model can be used as a tool for screening for movement disorders. The model was also pretty good at telling the difference between Parkinson's Disease and Essential Tremor. The researchers found out that even though smartphone sensors are not perfect and have some noise they can still provide signs of disease if they use a high-order filter and analyze the signals in the frequency domain. When the researchers were making the model, they found out that some movement features were better at predicting motor instability. Features like Spectral Magnitude Peak and Power Band Balance were important for detecting tremors. Other features, such as Harmonic Index Ratio helped tell the difference between Parkinson's and Essential Tremor.

The researchers used methods to classify the movement disorders and they found out that the LSVM and Ensemble Subspace KNN methods worked best for telling tremor patients from healthy people. The LSVM method worked best for telling the difference between Parkinson's and Essential Tremor when they used frequencies in the 3-10 Hz range. The Linear Support Vector Machine was also better because it did not use much power as the KNN method, which makes it good for use on mobile devices. This means that the model can be used for real-time screening without needing hardware. In the future the researchers want to use data from sensors to make the classification better and faster. They want to make an app that can help doctors make more accurate diagnoses of movement disorders. This is especially important in places were advanced diagnostic toolset not available.

The study helps make it possible for more people to have access to high-precision screening tools, which can improve accuracy. It can also be used in clinical practice to help doctors make more personalized and timely treatment decisions. The research shows that it is possible to get clinical information from standard devices, which can lead to automated AI-assisted long-term monitoring and better neuro-rehabilitation and global health practices. The researchers think that their work can make a difference in the way movement disorders are diagnosed and treated. They hope that their model can be used to help people over the world especially in places where it is hard to get access to good medical care. The model can be used on a device, which makes it easy to use anywhere. The study is a step forward in the use of machine learning for movement disorder diagnosis. The researchers are excited about the possibilities that their work has opened up. They hope that it will lead to better care for people, with movement disorders.

VI. CLINICAL IMPLICATIONS AND SOCIO-ECONOMIC IMPACT

The ability to use a machine learning model to diagnose diseases in world medical settings has big implications for healthcare systems around the world. Doctors often rely on tests like 123I-FP-CIT SPECT scans or special equipment for electromyography to tell the difference between Parkinson’s Disease and Essential Tremor. These tests are not always available in poorer areas making it hard for people in those regions to get proper care. This research shows how using the motion sensors in smartphones can help change that. These sensors are common and easy to access so they can make specialized neurological care widely available.

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This change has two benefits.
First it helps reduce healthcare costs by offering a tool that can screen for these conditions with accuracy and almost no extra cost.

Second it helps patients who live far from specialists avoid an difficult journey to get a correct diagnosis.'
The machine learning model achieves 97.2% accuracy in telling the difference between abnormal tremors making it act like a digital first step in the diagnostic process. This means only the likely cases get sent for expensive follow-up tests. The study also found that certain features like Spectral Magnitude Peak and Power Band Balance can be used not to diagnose but also to monitor machine learning model patients over time. In clinics doctors often make assessments based on their observations during brief visits usually every few months. With this system a mobile app can track a patient's movement continuously and more objectively.

For instance changes in a patients movement pattern can show how well treatments like medication or Deep Brain Stimulation are working. If a patients movement pattern improves after taking medication doctors get data to support their treatment decisions. This approach, known as Precision Neurology allows for personalized and timely care, which can improve the patient's life. By combining the accuracy of lab-based precision with the convenience of home use this research offers a way to scale up care for the growing number of age-related conditions. It ensures that quality diagnostic tools are available not just in big cities but across the globe making advanced care a standard part of healthcare everywhere. The machine learning model is going to make a difference in peoples lives by providing them with better care and more accurate diagnoses. This is especially important for people who live in poorer areas and do not have access to specialized care. The machine learning model is a tool that can help doctors diagnose and treat patients more effectively. It is a step forward for healthcare systems, around the world.

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